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TRANSFORMERS IN WILDFIRE DETECTION

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE ENGINEERING

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M.Sc. THESIS

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Nicosia
February, 2023

Approval

We certify that we have read the thesis submitted by **JUANITA JIDAI MAMZA** titled "**TRANSFORMERS IN WILDFIRE DETECTION**" and that in our combined opinion it is fully adequate, in scope, and quality, as a thesis for the Master degree in Artificial Intelligence.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

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Abstract

“TRANSFORMERS IN WILDFIRE DETECTION”

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In computer vision theory, research, and practical application, object detection is still crucial. The main source of inspiration for conventional object detection methods was machine learning. Convolutional neural networks (CNNs) have become the standard approach for deep learning-based computer vision tasks. However, attention-based vision transformer architectures have recently emerged as a promising alternative, showing superior performance to CNNs on various benchmark datasets for typical computer vision tasks like object detection, segmentation, and image classification.

However, despite their excellent outcomes, vision transformers have not been widely used in visual inspection in the actual world.

Due to its capacity to pretrain on enormous quantities of data and then transfer to smaller, more focused tasks via fine-tuning, transformers have emerged as the dominant paradigm in natural language processing. The Vision Transformer was the first significant effort to directly apply a pure transformer model to pictures as input, proving that transformer-based architectures can compete with convolutional networks on benchmark classification tasks. We can only use low-resolution inputs, though, due to the attention operator's computational cost. Maintaining a high input resolution is essential for increasingly difficult tasks like detection or segmentation so that models can accurately recognize and reflect tiny features in their output. Naturally, this prompts the query of whether transformer-based systems such

This study explores the efficacy of vision transformers in object detection tasks, utilizing them to provide image descriptors and training the resulting model with a metric learning objective that combines a contrastive loss and a differential entropy regularizer. The study compares the performance of vision transformer models and convolutional neural networks (CNNs) in wildfire detection applications with varying amounts of data. The results demonstrate that, with the right amount of data, vision transformers can outperform CNNs in object detection tasks, showing a consistent improvement over convolution-based methods. This research provides valuable insights into the potential of vision transformers as a superior alternative to traditional CNNs for object detection applications.

***Keywords*: ** DETR (Detection Transformer), Object Detection, Transformer, Image Classification, Machine learning

ÖZET

"TRANSFORMERS IN WILDFIRE DETECTION"

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Bilgisayarla görme teorisi, araştırma ve pratik uygulamada, nesne algılama hala çok önemlidir. Geleneksel nesne algılama yöntemlerinin ana ilham kaynağı makine öğrenimiydi. Evrişimli sinir ağları (CNN'ler), derin öğrenmeye dayalı bilgisayarla görme görevleri için standart yaklaşım haline geldi. Bununla birlikte, nesne algılama, segmentasyon ve görüntü sınıflandırma gibi tipik bilgisayarla görme görevleri için çeşitli kıyaslama veri kümelerinde CNN'lere göre üstün performans gösteren dikkat tabanlı görüntü dönüştürücü mimarileri son zamanlarda umut verici bir alternatif olarak ortaya çıkmıştır.

Bununla birlikte, mükemmel sonuçlarına rağmen, görüntü transformatörleri gerçek dünyada görsel incelemede yaygın olarak kullanılmamaktadır.

Muazzam miktarda veri üzerinde önceden eğitim verme ve ardından ince ayar yoluyla daha küçük, daha odaklı görevlere aktarma kapasitesi nedeniyle, dönüştürücüler doğal dil işlemede baskın paradigma olarak ortaya çıkmıştır. Vision Transformer, girdi olarak resimlere saf bir trafo modelini doğrudan uygulamak için ilk önemli çabaydı ve trafo tabanlı mimarilerin kıyaslama sınıflandırma görevlerinde evrişimli ağlarla rekabet edebileceğini kanıtladı. Dikkat operatörünün hesaplama maliyeti nedeniyle yalnızca düşük çözünürlüklü girdileri kullanabiliriz. Modellerin çıktılarındaki küçük özellikleri doğru bir şekilde tanıyabilmesi ve yansıtabilmesi için algılama veya segmentasyon gibi giderek zorlaşan görevler için yüksek bir giriş çözünürlüğünün korunması çok önemlidir. Doğal olarak bu, trafo tabanlı sistemlerin böyle olup olmadığı sorgusunu ister.

Bu çalışma, görüntü tanımlayıcıları sağlamak için bunları kullanarak ve kontrastlı bir kayıp ile diferansiyel entropi düzenleyiciyi birleştiren bir metrik öğrenme hedefiyle ortaya çıkan modeli eğiterek, görüntü dönüştürücülerin nesne algılama görevlerindeki etkinliğini araştırıyor. Çalışma, değişen miktarlarda veri içeren orman yangını algılama uygulamalarında görüntü dönüştürücü modellerinin ve evrişimli sinir ağlarının (CNN'ler) performansını karşılaştırıyor. Sonuçlar, doğru miktarda veriyle görüntü dönüştürücülerin nesne algılama görevlerinde CNN'lerden daha iyi performans gösterebileceğini ve evrişim tabanlı yöntemlere göre tutarlı bir gelişme gösterdiğini gösteriyor. Bu araştırma, nesne algılama uygulamaları için geleneksel CNN'lere üstün bir alternatif olarak görüntü dönüştürücülerin potansiyeline ilişkin değerli bilgiler sağlar.

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List of Abbreviations

CNN:	Convolutionary Neural Networks
ML:	Machine Learning
DeTr:	Detection Transformers
ViT:	Vision Transformer
SVM:	Support Vector Machine
DL:	Deep Learning
BIT:	Big Transfer
SGD:	Stochastic Gradient Descent
NVM:	Non-volatıle maemory

CHAPTER I

1. Introduction

1.1. Background of Study

A wildfire is an uncontrolled fire that occurs in an area of combustible vegetation, such as a forest, grassland, or prairie. Wildfires can be caused by natural events, such as lightning strikes, or by human activities, such as campfires, cigarettes, or fireworks. Wildfires can spread quickly and can be difficult to control, making them a significant threat to human life and property, as well as to the environment (Jain, 2020).

There are several factors that can contribute to the severity of a wildfire, including weather conditions, the type of vegetation present, and the topography of the area. Wind, low humidity, and high temperatures can all contribute to the rapid spread of a wildfire, while steep terrain and densely forested areas can make it difficult for firefighters to access the fire.

Wildfires can have a wide range of negative impacts, including loss of life, property damage, air quality issues, soil erosion, ecological damage, and economic loss. It's important to take steps to prevent wildfires and to have a plan in place to respond to them in order to minimize the damage they can cause (McWethy, (2019).

Wildfires are a natural calamity that occur on a global scale and cause significant economic damages as well as loss of life. Wildfires are expected to become more frequent in the years to come, primarily as a result of climate change, according to the predictions of experts (Marc Demange, 2022). The earlier a fire is detected and its spread is predicted, the more effectively it may be fought and impacted areas can be reduced. Several different kinds of fire detection systems have been developed. According to the statistics, both accidental and intentional forest fires cause terrible damage (Zhenyang Xue, 2022). They are responsible for suffering both personal and monetary losses, as well as causing the deaths of animals and the devastation of both forests and homes. Additionally, every year, fires consume between 350 million and 450 million hectares of land (Stay, 2019) . Therefore, a number of researchers concentrated their efforts on devising methods for the early detection of fires in order to lower the total number of adverse effects (Hosseini, 2022).

ML can be used in fire detection systems to improve their accuracy and efficiency. For example, machine learning algorithms can be trained on large datasets of images or video of fires, allowing them to recognize some features. This can be especially useful for vision-based fire detection systems, as the algorithms can automatically learn to distinguish between real fires and other sources of heat or light (Dampage, 2022) .In addition, ML algorithms can be used to analyse data from other fire detection technologies, such as smoke detectors and heat detectors, to identify patterns and trends that may indicate the presence of a fire. For example, a ML algorithm might be trained to recognize the characteristic rise in temperature that typically precedes a fire, allowing it to provide an early warning of a potential fire (Martinsson, 2022).

Conclusively, the use of ML in fire detection systems has the potential to improve the accuracy and efficiency of these systems, helping to reduce false alarms and improve response times (Kim, 2022) .In a similar vein, convolutional neural networks (often abbreviated as CNNs) are a sort of machine learning method that performs exceptionally well when applied to image recognition projects (Girshick, et al.) . They are able to distinguish the visible characteristics of fire, such as its form, dynamic texture and colour, which may be seen in still photos or videos and are employed in fire detection systems. To use a CNN for fire detection, the algorithm must first be trained on a large dataset of images or video of fires. During training, the CNN learns to recognize the visual features that are characteristic of fires, such as flickering flames and glowing embers. Once the CNN has been trained, it can be used to analyse new images or video to detect the presence of fire (Guan, 2022).

One advantage of using a CNN for fire detection is that the algorithm can learn to recognize a wide range of fire types and conditions, including different types of fuel and different stages of a fire (Almeida, 2022). This can help to improve the accuracy and reliability of the fire detection system. In addition, CNNs are generally able to process large amounts of data quickly, making them well-suited for real-time fire detection applications (Pincott, 2022) .The deployment of vision sensors has made it possible to conduct fire detection that is both more accurate and more efficient. Vision sensors have the ability to recognize visual characteristics of a fire, such as its form, colour, and dynamic texture (Khan Z. A., 2022). This can assist in lowering the number of false alarms and speeding up the reaction times. As a result of its ability to detect smoke and flames from a greater distance than previous technologies, they can additionally protect a larger geographical area (Muhammad K., 2019). However, it is essential to keep in mind that no one technique is fool proof; hence, current fire detection systems typically employ a number of distinct technologies working in tandem with one another in order to achieve the highest possible level of precision and dependability.

Detection transformers are a type of machine learning algorithm that can be used for object detection tasks, such as detecting fires in images or video. They are based on transformer neural networks, which are a type of deep learning architecture that was originally developed for natural language processing tasks (Wang W. J., 2022).To use a DeTr for fire detection, the algorithm must first be trained on a large dataset of images or video of fires. During training, the DeTr learns to recognize the visual features that are characteristic of fires, such as flickering flames and glowing embers. Once the detection transformer has been trained, it can be used to analyse new images or video to detect the presence of fire (Khudayberdiev, 2022).

One advantage of using a detection transformer for fire detection is that the algorithm can learn to recognize a wide range of fire types and conditions, including different types of fuel and different stages of a fire. This can help to improve the accuracy and reliability of the fire detection system (Swain, 2022) . In addition, detection transformers are generally able to process large amounts of data quickly, making them well-suited for real-time fire detection applications.

Furthermore, both convolutional neural networks (CNNs) and detection transformers can be used for fire detection tasks, such as detecting fires in images or video. Both types of algorithms are able to learn to recognize the visual features of fire, such as shape, colour, and dynamic texture, by being trained on a large dataset of images or video of fires (Majid, 2022) .One key difference between CNNs and detection transformers is the type of neural network architecture that they use. CNNs use a type of neural network architecture that is specifically designed for image recognition tasks, while detection transformers use a transformer neural network architecture, which was originally developed for natural language processing tasks (Yang, 2022).

Both CNNs and detection transformers have their own strengths and limitations, and which one is best suited for a given task will depend on the specific requirements of the application. In general, CNNs are well-suited for tasks that involve recognizing patterns and features in images, while detection transformers are well-suited for tasks that involve processing large amounts of data quickly and accurately (Li, 2022).

Detection transformers are a type of machine learning algorithm that can be used for object detection tasks, such as detecting fires in images or video. They are based on transformer neural networks, which are a type of deep learning architecture that was originally developed for natural language processing tasks (Wang Y. X., 2022).

There are several reasons why detection transformers may be useful for fire detection:

Improved accuracy: Detection transformers can learn to recognize a wide range of fire types and conditions, including different types of fuel and different stages of a fire. This can help to improve the accuracy of the fire detection system (Li Y. Z., 2022).

Fast processing: Detection transformers are generally able to process large amounts of data quickly, making them well-suited for real-time fire detection applications.

Adaptability: Detection transformers can learn to adapt to changing conditions and environments, which can be useful in fire detection systems that are deployed in a variety of different settings.

Overall, the use of detection transformers in fire detection systems has the potential to improve the accuracy and efficiency of these systems, helping to reduce false alarms and improve response times.

It's important to note that no single machine learning technique is necessarily the best choice for all fire detection tasks. The best approach will depend on the specific requirements of the application, such as the type of data being analysed, the desired level of accuracy, and the required processing speed. That being said, detection transformers may be particularly well-suited for fire detection tasks due to their ability to learn to recognize a wide range of fire types and conditions, their fast processing speed, and their adaptability to changing conditions. These characteristics may make them particularly useful for real-time fire detection applications, where quick and accurate processing is essential.

However, it's worth noting that detection transformers are relatively new and are still being actively researched and developed. As a result, it's possible that other machine learning techniques may be more suitable for certain fire detection tasks, depending on the specific requirements of the application. It's always a good idea to carefully evaluate the strengths and limitations of different machine learning techniques before deciding which one to use. In this research, we report the very first study that explores the capability of Transformers in the setting of forest fire segments using visible spectrum photos.

1.2. Statement of the problem:

For the detection of small, dense objects as well as objects with random geometric alterations, many existing techniques consistently exhibit poor performance. Experiments demonstrate that our proposed framework significantly increases the accuracy of recognizing small target objects with geometric deformation and the speed/accuracy trade-off.

1.3. Aim of the research:

The usage of transformer architectures presents an advantage in some types of object detection problems, not simply in terms of performance. The object detection algorithm predicts based on the image content by using this architecture. As a result, this method, where the images' context is crucial, has better success rates. For tasks involving object detection, it has been observed that recurrent neural networks perform less accurately and more slowly, because the processes are performed in order. We obtained a model that runs substantially faster since these actions are performed in parallel using transformer topologies.

1.4. Significance of the research:

Detection transformer technique will be utilized to predict images with fire in this thesis. Also included is the method for predicting the performance of the model and how well it does in different ResNets and layers and the quality of the results. We address two important research questions in this regard:

- How accurate will the prediction be?
- Are DeTr’s better than CNN’s?

1.5 Limitations of the Research

Previous research has examined the effects of the Transformer architecture's many drawbacks, including its inability to follow lengthy sequences and handle hierarchical inputs (Hahn, 2020) Access to Higher Level Representations is Limited. Transformers construct higher-level, more abstract representations of the input sequence layer by layer. The representations for the input sequence are handled concurrently at each layer. The highest-level representations from the past are therefore not used by a Transformer to calculate the representation for the present, even if these highest-level representations have previously been computed for autoregressive models.

1.6 Structure of the thesis

The thesis is split into six chapters, as well as a conclusion, an appendix, and references, make up the dissertation. An overview of the research and its setting is given in Chapter 1. Objects of the study, research techniques, etc.) Include a review of the literature on the main topic of the study. In Chapter 2's literature survey. The conceptual framework that will be needed to understand the rest of this thesis is introduced in this chapter. Reference to relevant works and comparison an overview of research methods and a description of the study's methodology are provided in Chapter 3. Chapter 4, provides an overview of the Performance and Result Analysis and in Chapter 5 the conclusion.

CHAPTER II

2.0. Literature Review

Wildfires can have a wide range of negative effects on the environment, wildlife, and human communities. Some examples of these effects include damage to or destruction of homes, buildings, and infrastructure. In other words, wildfires can cause significant damage to homes, buildings, and other structures, which can lead to displacement of residents and significant financial losses. Similarly, wildfires can destroy or damage habitats for a wide range of species, which can lead to declines in wildlife populations and a loss of biodiversity (Hoover, 2021).

Wildfires can create large amounts of smoke and other pollutants, which can negatively impact air quality and lead to health problems such as respiratory issues and eye irritation. Some of the major effects of wildfire are soil erosion, loss of vegetation, impact on water resources, psychological distress and economic impact (Goss, 2020).

2.1 History of wildfire detection using Artificial Intelligence.

The use of artificial intelligence (AI) for wildfire detection is a relatively recent development, but it has been rapidly advancing in recent years.

In the early 2000s, researchers began using AI techniques, such as neural networks, to analyse satellite imagery to detect signs of wildfire. These early systems used simple algorithms and could only detect large wildfires that were easily visible from space (Shi, (2020)).

In the 2010s, advances in machine learning and computer vision allowed for the development of more sophisticated wildfire detection systems. Researchers began using deep learning algorithms to analyse large amounts of data from a variety of sources, such as satellite imagery, weather data, and social media, to detect patterns and trends that may indicate a wildfire (Kaul, 2020).

In recent years, the use of AI in wildfire detection has continued to advance, with new technologies such as Lidar and Infrared imaging being used to detect wildfire, and the integration of multiple data sources to improve the accuracy and speed of wildfire detection.

In 2020 and 2021, AI-based wildfire detection systems were actively used to detect and monitor wildfires, especially in the western part of the United States. These systems have proven to be effective in detecting wildfires early, allowing for a rapid response and reducing the damage caused by the fires (Haenlein, 2019).

Therefore, the history of using AI for wildfire detection has been one of rapid progress and improvement, and it is expected that the use of AI in this field will continue to grow in the future, with the development of more advanced and sophisticated systems.

2.2 Wildfire Detection using AI:

Artificial intelligence (AI) can be used to detect and monitor wildfires in a number of ways. Some examples include:

- ***Satellite imagery analysis:*** AI algorithms can be used to analyze satellite imagery of an area to identify signs of a wildfire, such as changes in vegetation or an increase in temperature (A. Buslaev, 2018).
- ***Drone-based detection:*** Drones equipped with cameras and thermal imaging sensors can be used to detect and monitor wildfires in real-time, and AI algorithms can be used to process the data collected by these drones (Mubarak, et al., 2022) .
- ***Social media monitoring:*** AI algorithms can be used to monitor social media for posts and photos that may indicate a wildfire, such as images of smoke or flames (Davies, 2022) .
- ***Automatic detection from cameras:*** AI algorithms can be used to analyze video footage from cameras placed in strategic locations to detect signs of wildfire.
- ***Predictive modelling:*** AI algorithms can be used to create models that predict the likelihood of a wildfire occurring in a particular area based on factors such as weather conditions, vegetation type, and past fire history (Gaur, 2020).
- ***Automatic alert systems:*** AI can be used to automatically trigger an alert to emergency services when a wildfire is detected, allowing for a rapid response.
- ***Deep learning algorithms:*** AI algorithms are used in analyzing patterns in image and to detect early signs of a wildfire and predict its likely path, which can help emergency services respond more quickly and effectively (Wu, 2022.).

2.3 Advanced Wildfire Detection Techniques:

Advanced wildfire detection techniques use a combination of advanced technology and data analysis to improve the accuracy and speed of wildfire detection. Some examples include:

- ***Lidar:*** Lidar which includes light ranging and detecting is used as a technology sensing remote which makes use of laser beams to map the terrain and detect changes in vegetation. It can be used to detect signs of a wildfire, such as changes in vegetation density or the presence of smoke.
- ***Infrared imaging:*** Infrared imaging cameras can be used to detect heat signatures from a wildfire, even at night or in poor visibility conditions (Wilk-Jakubowski J. e., 2022).
- ***Radar:*** Radar can be used to detect the presence of smoke by analyzing the way radio waves are scattered by smoke particles in the air (Ban, 1322).
- ***Machine learning:*** Machine learning algorithms are often used to examine significant quota of data from a variety of sources, such as satellite imagery, weather data, and social media, to detect patterns and trends that may indicate a wildfire.
- ***Computer vision:*** Computer vision algorithms can be used to automatically analyze images and videos from cameras, drones, and other sources to detect signs of wildfire, such as flames or smoke (Chen, 2022) In artificial intelligence and computer vision, an important topic of research is object detection. Identifying the actual target of interest within an image are the main objectives, choosing the proper group, and providing the necessary bounding box for individual targets. The tasks in very modern computer vision includes; object detection, target tracking, pattern recognition and semantic scene interpretation call for it (Saleh, Ameen, Altrjman, & Al-Turjman, 2022).
- ***Automated drones:*** Autonomous drones equipped with cameras, thermal imaging sensors, and other sensors can be used to detect and monitor wildfires in real-time (Yuan, 2015).
- ***Internet of Things (IoT) devices:*** IoT devices such as sensors and cameras can be placed in strategic locations to detect and monitor wildfire. The data

collected can be analyzed in real-time using AI algorithms (A. S. Mubarak, 2021).

- ***Integration of multiple data source:*** Combining multiple data sources such as satellite imagery, weather data, social media, and ground-based observations can help to improve the accuracy and speed of wildfire detection, as well as provide a more comprehensive understanding of the wildfire (Mahmoud, 2019).

2.4 Deep Learning in Wildfire Detection:

Using this learning approach; convolutional neural networks (CNNs) and detection transformers, have been widely used in segmentation and also in fire detection. To use this approach for detecting fire and segmentation, the algorithm must first be trained on a large dataset of images or video of fires. During training, the algorithm learns to recognize the visual features that are characteristic of fires, such as flickering flames and glowing embers. Once the algorithm has been trained, it can be used to analyse new aerial images to detect the presence and location of fires (Barmpoutis, 2020).

One advantage of using deep learning approaches for fire detection and segmentation is that they can learn to recognize a variety of fire types combined with conditions, which includes different types of fuel and different stages of a fire. This can help to improve the accuracy together with reliability of the fire detection system. In addition, deep learning approaches are generally capable of processing significant quotas of data speedily, and therefore making them well-suited for real-time fire detection applications. However, it is worthwhile to understand the effectiveness of a deep learning approach for fire detection and segmentation. Careful evaluation and testing will be necessary to determine the most suitable approach for a given task. here are several deep learning approaches that have been proposed for fire detection, which can be grouped into the following categories:

- ***Convolutional neural networks (CNNs):*** These are another variance of deep learning algorithm though they are primarily designed for tasks such as image recognition. They may be taught to distinguish the visual characteristics of fire by being trained on a huge dataset of aerial photos of fires. These characteristics include the texture, color and shape of fire (Naser, 2021).

- ***Object detection algorithms:*** These are another variance of deep learning algorithm designed to locate and classify objects in images or video. Object detection algorithms, such as YOLO and R-CNN, can be trained on a large dataset of aerial images of fires to learn to recognize the location and extent of fires in new images (Mariano, 2002, August) .
- ***Detection transformers:*** These are another variance deep learning algorithm based on transformer neural networks, which were originally developed for natural language processing tasks. Detection transformers can be trained on a large dataset of aerial images of fires to learn to recognize the visual features of fire and to locate and classify fires in new images (Jadon, 2020).

Overall, each of these methods has a unique set of benefits and drawbacks, and the one that is most appropriate for a particular activity will be determined by the particular needs that are imposed by the application.

To classify wildfires, the research carried out by (Ghali, Akhloufi, & M. A., 2022) implements an innovative deep learning strategy that makes use of the EfficienNet-B5 and DenseNet-201 models. In the course of their research, scientists made use of two vision transformers known as TransUNet and TransFire in addition to a deep convolutional model in order to forecast the locations of fires. Their findings demonstrated segmentation models, with F1-scores of 99.9% and 99.82% for TransUNet and TransFire respectively. Similar to this study, (Ghali, et al., 2021) addresses early segmentation and detection in forest fires to predict the spread and assist in firefighting. In their study, they proposed model to classify the wildfire with accuracy of 85.12%. F1-score of 99.9% and 99.82% for both TranUNet and TransFire.

2.5 Deep Learning methods For Fire Categorization:

Deep learning approaches for fire classification, it involves classifying fires in images or video as either present or absent. This can be useful for identifying areas where fires are likely to occur, or for monitoring the spread of fires over time [23].

There are several deep learning algorithms that can be used for fire classification, including CNNs, SVMs, and decision trees. These algorithms can be trained on a large dataset of images or video of fires and non-fires to learn to recognize the visual features that are characteristic of fires (Khan, et al., June 2021) .In order to apply a deep learning algorithm for fire classification, the method must first be trained on a large dataset consisting of photos or video of fires and non-fires. Only after this can the algorithm be used for fire classification. During the training process, the algorithm is taught to recognize the various visual aspects that are typical of fires, such as the smoldering flames and the glowing embers. Once the algorithm has been taught, it may be used to determine whether or not a new image or video contains a fire based on whether or not it was previously trained on fires. Therefore, the use of deep learning approaches for fire classification can help to improve the accuracy and efficiency of fire detection systems, helping to reduce false alarms and improve response times (Bouguettaya, et al., 2022).

In the past ten years, deep Learning techniques have witnessed exploding triumph in various computer vision applications, including object detection, medical diagnosis, road monitoring e.t.c. These activities fall under the category of computer vision (Athanasios Voulodimos, 2018) . This is mostly the result of the rich feature map that was created by utilizing convolutional layers. The task of object segmentation was successfully accomplished by DL algorithms, which were able to accurately categorize each pixel throughout the entire image and establish the precise shape of the items. They achieved results that were superior than those of traditional machine learning models.

Numerous studies have been conducted over the course of several years to investigate the topic of fire detection using methods of deep learning (G, Chetan, Abhishek, Digvijay, & Prajwal, 2020) . The SFEwAN-SD system sounds like a promising approach for detecting fire using UAVs. It's interesting to see how the use of different helix neural networks can allow for the extraction of different types of features from the input images, with one CNN focusing on shape and texture and another focusing on colour and texture. The use of the ReLU activation function in the second CNN is also noteworthy, as it has been found to improve the training speed of deep neural networks and can lead to better efficiency on a vast range for the tasks. It's good to see that the processing time and accuracy of this system were superior to those of other strategies at the time of its development (B. Xu, 2015).

2.6 Transformers Applications

Self-attention for object detection: Being the first method to successfully use transformers for the object detection job, DETR (Nicolas Carion F. M., 2020) is noteworthy. Its method is unique for not requiring non-maximum suppression (NMS) because their decoder design learns to eliminate redundant bounding box predictions on its own.

Deformable DETR (Xizhou Zhu, 2020) addresses a few of the drawbacks of DETR:

1) attaining relatively poor detection performance on small objects and

2) necessitating substantially longer training epochs for convergence than normal detectors. Introducing a deformable attention module that learns to pay attention to a small selection of sampling sites in the feature map, Deformable DETR solves the problems that are mostly caused by prohibitive complexity in processing high-resolution feature maps. RelationNet++ [7] (Cheng Chi, 2020) proposes a "Bridging Visual Representations" (BVR) module based on a Transformer decoder for integrating data from several object representations, using multi-head attention in a new way. The aforementioned studies expand on earlier efforts by RelationNet (Han Hu, 2018, pp. 3588–3597)) and Non-Local Networks (NL) to recognize objects by paying attention to bounding box features and pixel features, respectively.

Convolutional networks are used by DETR and Deformable DETR to encode visual features, while the Transformer is used to decode those features into detection outputs (Ren, He, Girshick, Sun, & Jian, 2015).

Self-attention for visual representations: The first pure Transformer-based visual model to match state-of-the-art convolutional networks in image recognition performance is ViT. (Alexey Dosovitskiy, 2020.)When ViT is initially pretrained on a big dataset and then applied to tasks with fewer datapoints, in particular, it shows exceptional performance. The technique has yet to be demonstrated to be generalizable to spatial problems like object detection or image segmentation, despite its success in image recognition.

An unsupervised generative pretraining method for learning robust visual representations is called Image GPT (iGPT). (Mark Chen, 2020) Despite the input image resolution being very low in their method, applying a GPT-2 (Alec Radford, 2019) based model directly to the image pixels was demonstrated to produce convincing image completions and samples, demonstrating that a totally Transformer-based architecture is feasible for some visual applications.

Other studies have examined the limitations of convolutional neural networks (Zhang R. , 2019) , (Katherine Hermann, 2020) as well as the connection between self-attention modules and convolutional layers (Mike Lewis, et al., 2019).

Pretraining and self-training: Several studies have looked at the efficiency of pretraining for visual representation learning on large-scale picture datasets as JFT-300M (Chen Sun, 2017) and IG-940M (Dhruv Mahajan, 2018) . Large-scale classification-based pretraining was found to improve detection transfer performance in Big Transfer (BiT). Other studies have discovered that, when the detection dataset is sufficiently big, smaller-scale classification-based pretraining, such as pretraining on ILSVRC-2012 (Jia Deng, 2009), does not always improve detection performance compared to training from scratch.

2.7 Machine Learning Classification:

In machine learning, classification is the task of assigning a class label to an input sample based on its features. For example, a classifier might be trained to predict whether an email is spam or not spam based on the contents of the email.

There are many different algorithms that can be used for classification, including logistic regression, support vector machines (SVMs), and decision trees (Sebe, 2017). To train a classifier, you need to have a labelled dataset of training examples, where each example includes the features of the input sample and the corresponding class label. The classifier is then trained on this dataset by adjusting the model parameters so that it can accurately predict the class labels for the training examples. After training, the classifier can be tested on a separate dataset of test examples to evaluate its performance. Common evaluation metrics for classification include accuracy, precision, and recall.

Models for detecting traffic often make use of several types of neural networks, including convolutional neural networks, gated recurrent units, long short-term memories, recurrent neural networks and Bayesian networks. In intelligent environments, sensors are used to collect data, which is then subjected to analysis and prediction. The convolutional neural network, often known as the CNN, is able to successfully fulfil a number of tasks for successful object detection. One of these jobs is feature extraction (Zhang F. W., 2018).

Through supervised learning, a deep convolutional neural network is able to differentiate between different people's faces when provided with a large number of photographs of their faces. (Bond, 2019). The only challenge that arises with computer vision and machine learning applications is the annotation and labelling of the data. The way that machine learning algorithms are carried out in the cloud at the moment is referred to as "cloud machine learning" or "machine learning as a service."

Recent studies have concentrated their attention on a number of extremely important fields, such as computer vision and machine learning. The picture and pattern mappings are what the computer vision system looks at in order to determine the answers (Esposito, 2001).

2.8 Classification Algorithms:

Classification algorithms vary in machine learning, and the best choice for a particular problem depends on the nature of the data and the requirements of the application. Some popular classification algorithms include:

Logistic Regression: It is a model that is used for binary classification (i.e., predicting a class label that can take on two values). It is based on the idea of using a linear combination of the input features to predict the probability that a given sample belongs to a particular class.

Support Vector Machines (SVMs): These are algorithms that find the hyperplane in a high-dimensional space that maximally separates the classes. They are effective in high-dimensional spaces and can be used for binary or multi-class classification (Kulkarni, 2017).

Decision Trees: These are algorithms that create a tree-like model of decisions based on the input features. At each node in the tree, the algorithm selects a feature and a threshold value, and then splits the data based on whether the feature value is below or above the threshold (Kotsiantis, 2007). The process is repeated at each subsequent node until the leaves of the tree represent class labels.

K-Nearest Neighbours (KNN): This is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance). It is a lazy learner, meaning it does not learn a discriminative function from the training data but simply memorizes the training instances.

Naive Bayes: This is a probabilistic classifier based on the Bayes theorem, which states that the probability of a hypothesis (e.g., a class label) given some evidence (e.g., input features) (Duda R.O., 1973) . It is often used for text classification and medical diagnosis.

Random Forests: These are ensembles of decision trees, where each tree is trained on a different random subset of the training data. The final prediction is made by averaging the predictions of all the trees (Pal, 2005).

Neural Networks: These are networks of interconnected nodes that are inspired by the structure and function of the brain. They can be used for classification tasks, especially when the input data is high-dimensional or has a complex structure (Arsha, et al., 2018) .

2.9 Deep Learning Classification:

DL g is a machine learning subfield that is inspired by the structure and function of the brain, specifically the neural networks that make up the brain. Deep learning models learn and show very difficult patterns in data, and as a result, they have been successful in a wide range of applications, including image and speech recognition, natural language processing, and machine translation (LeCun, 2015).

Deep learning models can be used for classification tasks, where the goal is to assign a class label to an input sample based on its features. One type of deep learning model that is commonly used for classification is the convolutional neural network (CNN). CNNs are particularly well-suited for image classification tasks, as they are able to learn and extract features from images directly, without the need for manual feature engineering (Li Y. S., 2022).

To train a deep learning classifier, you need a large dataset of labelled examples that the model can use to learn the relationship between the input features and the class labels. The model is then trained using an optimization algorithm, such as stochastic gradient descent (SGD), to adjust the model parameters so that it can accurately predict the class labels for the training examples.

After training, the deep learning classifier can be tested on a separate dataset of test examples to evaluate its performance. Common evaluation metrics for classification include accuracy, precision, and recall (Priyanka, 2022).

2.9.1 Deep Learning algorithm:

Deep learning algorithms are a type of machine learning algorithm that is inspired by the structure and function of the brain, specifically the neural networks that make up the brain. Deep learning algorithms are able to learn and represent very complex patterns in data, and as a result, they have been successful in a wide range of applications, including image and speech recognition, natural language processing, and machine translation (Wilk-Jakubowski J. S., 2022).

There are several types of deep learning algorithms, including:

Convolutional Neural Networks (CNNs): These are algorithms that are particularly well-suited for image and video data. They are made up of multiple layers of interconnected nodes, and each layer is responsible for learning a different set of features from the input data. Evolutionary neural networks (CNNs) are used to train computers to recognize and segment objects that are highly complex but lack sufficient knowledge about their edges and contours. Because of its obvious network structure, high robustness, and simultaneous recognition and segmentation processing, Maskrcnn is a promising model for industrial picture identification (Auwalu Saleh Mubarak, Zubaida Said Ameen, & Al-Turjman., 2023).

(RNNs) Recurrent Neural Networks: They are algorithms that process sequential data, which include time series or natural language. They have memory cells that allow them to retain information from previous time steps and use it to make predictions at the current time step.

Autoencoders: These are the algorithms used for feature learning and dimension reduction. They include of an encoder and a decoder, and the purpose is to learn a compressed version of the input data that can be used to properly reconstruct the original data (Seydi, 2022).

Generative Adversarial Networks (GANs): These are algorithms that are used for generating synthetic data that is similar to a training dataset. They consist of two networks, a generator and a discriminator, that are trained to work together in a zero-sum game.

Deep learning algorithms are typically trained using large datasets and an optimization algorithm, such as stochastic gradient descent (SGD), to adjust the model parameters so that the algorithm can accurately predict the outputs for the training examples. After training, the deep learning algorithm can be tested on a separate dataset of test examples to evaluate its performance (Rekavandi, 2022).

2.9.2 DETR Transformer

DETR (Detection TRansformer) is a transformer-based architecture for object detection developed by Facebook AI. It was introduced in the paper "End-to-End Object Detection with Transformers" (https://arxiv.org/abs/2005.12872). In traditional object detection systems, the process of identifying and localizing objects in an image or video involves multiple stages, including feature extraction, region proposal generation, and classification. DETR simplifies this process by using a transformer-based architecture to directly predict object classes and bounding boxes from the input data, without the need for multiple stages.

The key idea behind DETR is to use a transformer to encode the input image into a set of feature maps, which are then processed by a series of convolutional layers to produce a set of object queries, each of which corresponds to a particular object class. The transformer then decodes the queries to predict the object class and bounding box for each object (Vaswani, et al., 2017). DETR has been shown to achieve state-of-the-art performance on several object detection benchmarks, including COCO and Pascal VOC. It has the advantages of being faster and more accurate than traditional object detection systems, and it is also easier to train and fine-tune.

CHAPTER III

3. Methodology

3.1.1. Study Design:

This study adopts and illustrates the imperative application of a detection transformer utilized in wildfire detection. We provide a description of the models used for our wildfire detection, together with the training dataset, evaluation metrics, and the work's evaluation criteria.

3.2 Data acquisition:

We performed experiments on Wildfire datasets gathered from kaggle in the form Pascal Voc. The datasets are split into Training, validation and test, containing 440 images: 390(1.2k) training set, 25(50) validation set and 25(50) testing set amounting to a ratio of 90%, 5% and 5% respectively. Size of the images were 416 x 416. We added augmentations to the training set resulting in 3 images per training image.

Each image was annotated with bounding boxes to capture where the fire. The model was implemented with Roboflow using their object detection toolbox which offers modularity for models and train/tests pipelines. The models were trained for 30 epochs on google collabs k80 GPU with 12GB memory. By doing so we utilized the full capacity of the hardware.

In this experiment, we trained the wildfire dataset with 1.2k images which has already been split into validation, testing and training. The dataset set is then trained on different parameters which include the encode-decoder, ResNets and Number of heads.

Encoder-Decoder: In the training we fine-tuned the number of encoders between 3,6 and 12 while maintaining the decoders number as 1. For the second we the number of Decoders were changed between 3,6 and 12 also while maintain the number of encoders as 1. Number of Attention Heads: In order to get a wide range of results, we fine-tune the architecture of the Transformer by changing the number of heads.

3.3 Method

In this study, we discussed the model that we used for the task of detecting wildfires. In addition, we offer the dataset that was utilized for training purposes and the evaluation criteria that were used. There are still some problems in explicitly modelling long-range dependency, however the detection transformer object-detection prediction has developed as an alternative architecture to existing ConvNet models.

In addition to that, we will present the ResNet model that was utilized. The effectiveness of our method is judged using two FPN backbones, which are (ResNet-5o and ResNet-101). On a GPU, we train the models for a total of thirty iterations. In order to achieve different and the best results we train the datasets on different number of encoders-decoder, ResNet 50 and 101 and different number of heads.

For the first sets of training the Encoder is set to 1, while the Decoder is changed between the numbers 3,6 and 12 while maintaining the same number of encoders. It is then trained on the two ResNets and Attention Heads 4,8 and 12.

The second set of training is the reverse of the first. The Decoder is the changed between 3,6 and 12 while maintaining the Encoder number 1. It is also trained on the two ResNets used here and Attention Heads 4,8 and 12.

Table 1:Datasubset for classification

Dataset	Fire Images
Training set	1200
Validation set	49
Testing set	58

3.4 DETR Architecture:

The architecture of the DETR (DEtection TRansformer) model is based on the transformer, a type of neural network architecture that was developed for natural language tasks. The transformer embeds the encoder and a decoder, which are both made up of multiple layers of attention and fully connected (FC) blocks.

In the DETR model, the encoder takes an input image and processes it using a series of convolutional and maxpooling layers to produce a set of feature maps. The feature maps are then fed into the transformer encoder, which consists of multiple layers of self-attention and FC blocks. The self-attention layers allow the transformer to attend to different parts of the input image and learn global dependencies between the input features.

The output of the transformer encoder is a set of feature maps, which are processed by a series of convolutional and up sampling layers to produce a set of object queries, each of which corresponds to a particular object class. The queries are then fed into the transformer decoder, which consists of multiple layers of self-attention, encoder-decoder attention, and FC blocks. The encoder-decoder attention layers allow the decoder to attend to the feature maps produced by the encoder and use them to refine the object queries.

The output of the transformer decoder is a set of object class and bounding box predictions for each object in the input image. The predictions are processed by a series of convolutional and up sampling layers to produce a final set of class and bounding box maps, which are used to generate the final object detections.

Therefore, as in figure 1, the DETR model is able to directly predict object classes and bounding boxes from the input image, without the need for multiple stages or hand-crafted features. This makes it faster and more accurate than traditional object detection systems.

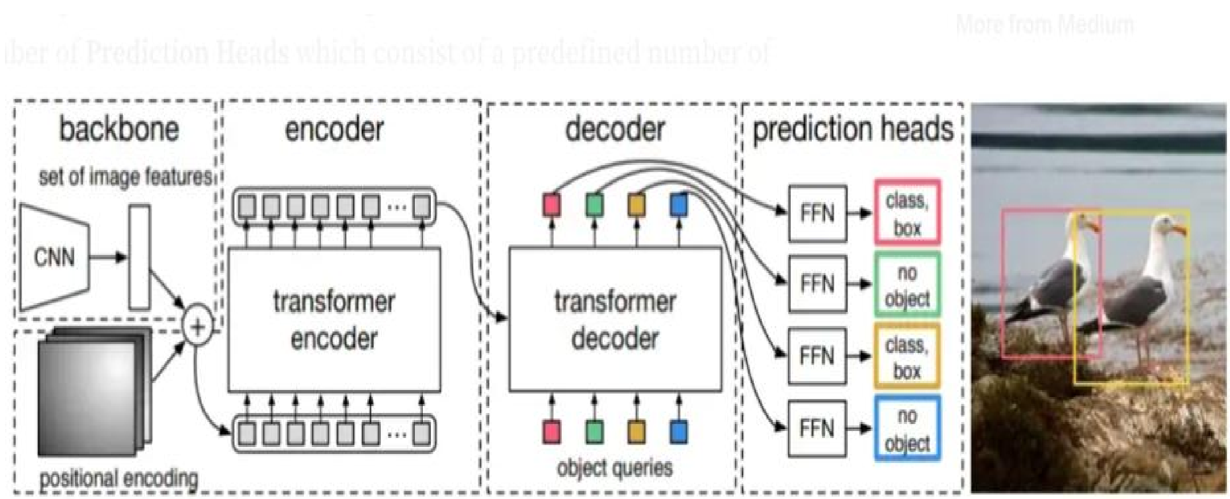


Figure 1: DETR architecture

3.5 The Model:

ResNet 50 and ResNet 100 were utilized for this study. The ResNet 50 and ResNet 100 are convolutional neural network (CNN) architectures that were developed by Microsoft Research for image classification tasks. They are part of the ResNet family of CNNs, which are known for their ability to achieve very deep network depths (i.e., many layers) while still being able to train effectively and achieve good performance. ResNet 50 and ResNet 100 are similar in terms of their overall architecture, but they differ in the number of layers they contain. ResNet 50 has 50 layers, while ResNet 100 has 100 layers. Both architectures use skip connections, which allow the network to bypass one or more layers and directly access deeper layers, as a way to address the problem of vanishing gradients that can occur in very deep networks.

ResNet 50 and ResNet 100 have been widely used in a variety of image classification tasks, and they have achieved state-of-the-art performance on several benchmarks (K. He, 2016). They have also been used for tasks such as object detection and semantic segmentation, where they have been effective as feature extractors or as part of a larger model.

The ResNet 50 and ResNet 100 could also be used for fire detection tasks, as they have the ability to learn and extract features from images. However, it is important to note that the performance of a model depends on the specific task and dataset, and it may be necessary to fine-tune the model or use additional techniques, such as data augmentation or transfer learning, to achieve good performance.

3.6 Feature Extraction:

In a transformer-based object detector, such as DETR (DEtection TRansformer), feature extraction refers to the process of extracting meaningful features from the input data that can be used to identify and locate objects in the data (G. Kumar and P. K. Bhatia, 2014). In DETR, the input data is typically an image or a sequence of images, and the features are extracted using a combination of convolutional and self-attention layers. The convolutional layers are responsible for learning local features from the input data, while the self-attention layers allow the model to attend to different parts of the input data and learn global dependencies between the features.

The extracted features are then processed by a series of convolutional and up sampling layers to produce a set of object queries, each of which corresponds to a particular object class. The queries are fed into the transformer decoder, which uses them to predict the object class and bounding box for each object.

Therefore, the feature extraction process in a transformer-based object detector is an important step in the object detection process, as it allows the model to learn and extract relevant features from the input data that can be used to make accurate predictions.

3.6 Feature selection:

Feature selection is the process of selecting a subset of relevant features from a larger set of features for use in a machine learning model. The goal of feature selection is to improve the performance of the model by reducing the dimensionality of the data, reducing overfitting, and improving the interpretability of the model.

In a transformer-based object detector, such as DETR (DEtection TRansformer), feature selection is typically not a separate step, as the model is able to learn and extract relevant features directly from the input data. However, it is still possible to use feature selection methods to select a subset of the features learned by the model for use in downstream tasks, such as object classification or object tracking.

There are several feature selection methods that can be used, such as filter methods, which select features based on statistical measures of relevance, and wrapper methods, which select features based on the performance of the model when trained on different subsets of features.

It is important to note that feature selection should be carefully considered when using a transformer-based object detector, as the performance of the model may be sensitive to the choice of features (Zhang F. W., 2018). In some cases, using a larger set of features may be beneficial, while in other cases, a smaller set of features may be more effective.

CHAPTER IV

4.0. Result and Discussion

For the wildfire detection, we created a dataset on Roboflow and trained the proposed models on a k80 GPU with 12GB memory The learning data were split as follows: 1200 images for training, 50 images for validation, and 50 images for testing.

In order to determine the best weights for each model, checkpoints here saved every [5] epochs from 30 epoch and evaluated. Each ResNets were trained on different attention heads and 3 different encoder and decoder numbers.

Table 2 presents a comparative analysis of our proposed method with the dataset and we can also view the best performance the method achieved (accuracy of mAP-50 at 73.73) thanks to the ResNet 50 and 101 models. Although it may not have outperformed other models such as the TransUNet-Res50-ViT, TransUNet-ViT and MedT due to the large datatset that those models are being trained on which provides better results, it has achieved better accuracy and performances compared to deep CNNs U22-Net, U-Net, and EfficientSeg and some other ML methods.

Another difference between this proposed method and some of the ML learning methods mentioned above is that the images and the classes are able to show the differences between different shapes and structures of how the fires look like while some of the other methods prefer to use pixel segmentation which may require more and more training.

Below is the table and performance evaluation of our proposed model:

	Encoder	Decoder	Heads	All	MAP-50	MAP-75
ResNet50	1	3	4	50.05	63.65	44.22
	1	6	4	42.6	65.27	17.13
	1	12	4	48.66	69.59	34.96
ResNet101	1	3	4	53.86	72.38	38.44
	1	6	4	45.79	65.54	20.26
	1	12	4	40.21	58.93	7.88
ResNet50	1	3	8	52.87	66.42	46.97
	1	6	8	49.85	62.91	37.04
	1	12	8	55.08	65.98	45.71
ResNet101	1	3	8	52.38	69.27	42.53
	1	6	8	48.69	62.05	41.9
	1	12	8	50	67.54	29.34
ResNet50	1	3	12	55.52	71.54	53.75
	1	6	12	54.65	74.71	48.39
	1	12	12	50.25	64.01	37.46
ResNet101	1	3	12	51.3	68.02	31.33
	1	6	12	49.74	69.18	29.73
	1	12	12	48.97	66.23	30.2
ResNet50	3	1	4	52.7	66.23	45.95
	6	1	4	50.28	71.29	27.14
	12	1	4	46.69	70	40
ResNet101	3	1	4	51.11	65.12	37.76
	6	1	4	51.92	65.5	41.62
	12	1	4	53.47	73.7	45.19
ResNet50	3	1	8	52.71	68.74	40.19
	6	1	8	50.25	69.2	35.05
	12	1	8	54.2	70.19	44.97
ResNet101	3	1	8	50.1	63.11	41.42
	6	1	8	0.18	70.23	33.75
	12	1	8	53.08	72.86	48.32
ResNet50	3	1	12	50.32	69.59	29.58
	6	1	12	56.93	73.73	53.93
	12	1	12	50.55	61.32	46.57

ResNet101	3	1	12	52.51	70.77	44.57
	6	1	12	51.31	71.93	40.31
	12	1	12	51.07	72.71	55.18

Table 2. *Performance evaluation of wildfire classification models*

Table 2 presents the results from an experiment comparing different configurations of a transformer model. The columns in the table are: "Encoder", "Decoder", "Heads", "All", "50", and "75".

Encoder: The number of layers in the encoder part of the transformer model.

Decoder: The number of layers in the decoder part of the transformer model.

Heads: The number of attention heads used in the model.

All: performance metric that is measured across all test data.

50: performance metric that is measured on a subset of the test data.

75: performance metric that is measured on a subset of the test data.

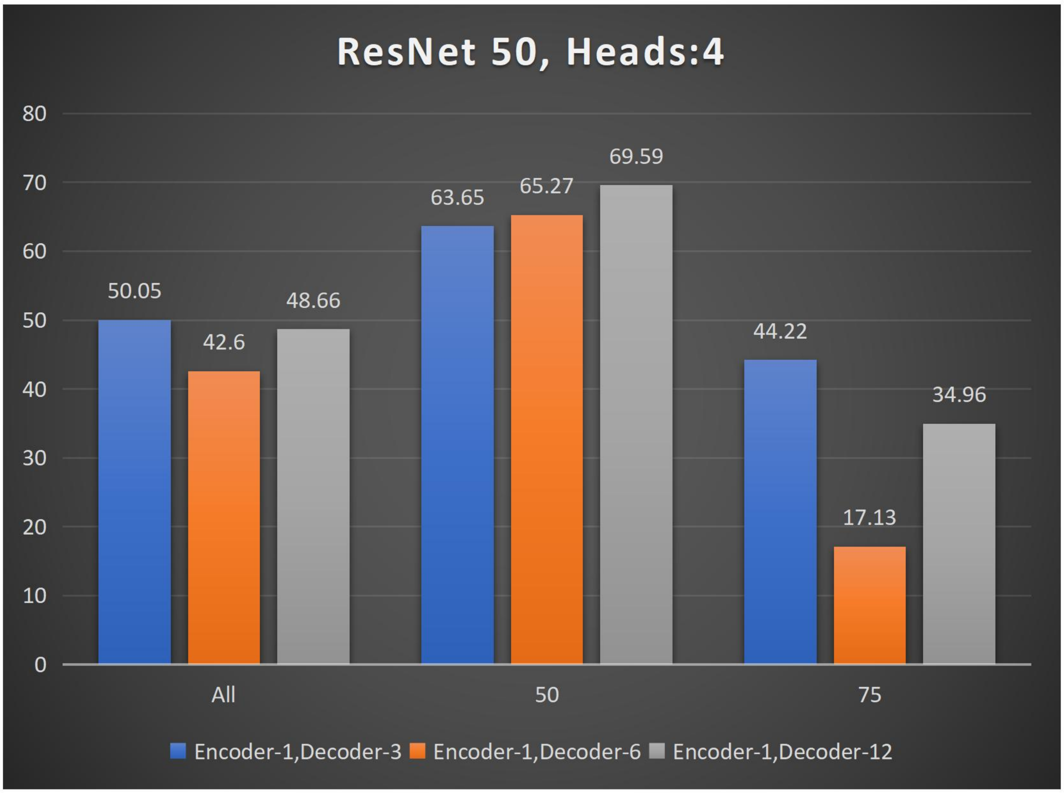
The rows in the table are split into two sections, one for ResNet50 and one for ResNet101. ResNet50 and ResNet101 are different architectures of the model.

The performance metric is the accuracy of the model, and it's being evaluated on different configurations of the transformer model. Based on the values in the table, it can be seen that increasing the number of layers in the encoder, decoder, and attention heads generally leads to improved performance. However, the specific impact of these factors on performance may vary depending on the architecture of the model.

Table 3: Comparative analysis using Attention heads 4

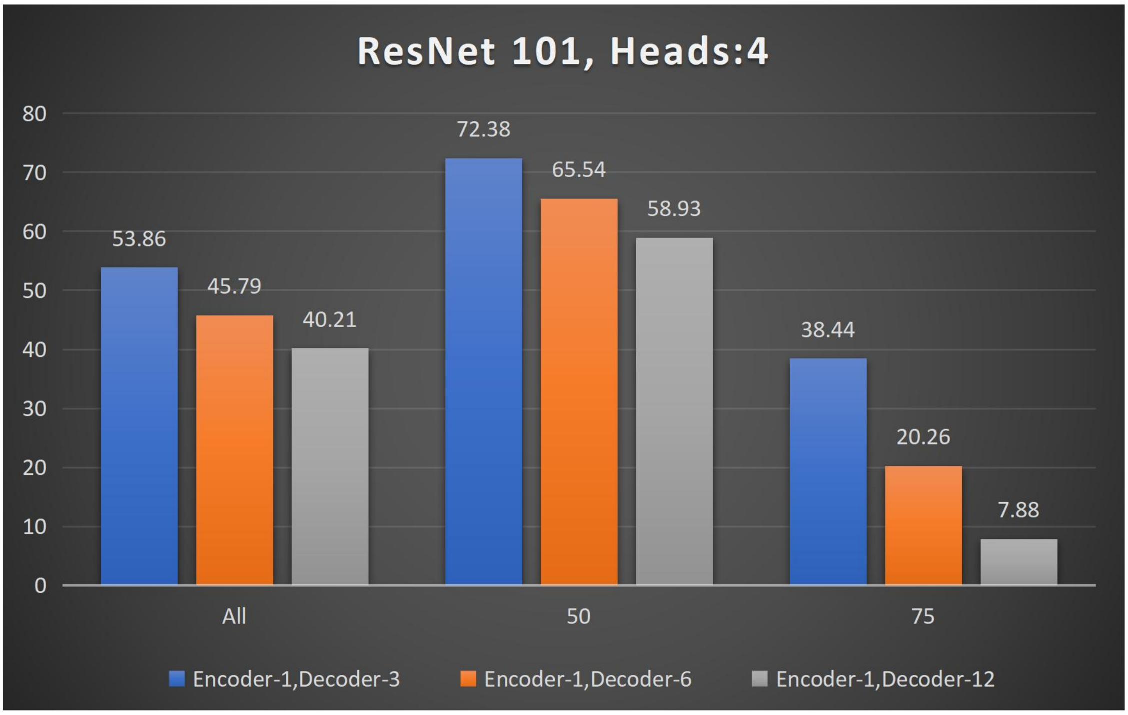
	Encoder	Decoder	Heads	All	MAP-50	MAP-75
ResNet50	1	3	4	50.05	63.65	44.22
	1	6	4	42.6	65.27	17.13
	1	12	4	48.66	69.59	34.96
ResNet101	1	3	4	53.86	72.38	38.44
	1	6	4	45.79	65.54	20.26
	1	12	4	40.21	58.93	7.88

Figure 2: *Bar chart representation at ResNet50 using Attention heads 4,Encoder 1, Decoder 3,6 and 12*



The Resnets50 with number of heads 4, Decoder 3,6&12. The detr achieves the highest mAP of 50.05, mAP-50 63.65 and mAP-75 44.22 at Decoder 3. The lowest detr at Decoder 6 mAP 42.60 , mAP-50 65.65 and mAP-75 17.13.

Figure 3: *Bar chart representation at ResNet101 using Attention heads 4,Encoder 1, Decoder 3,6 and 12*

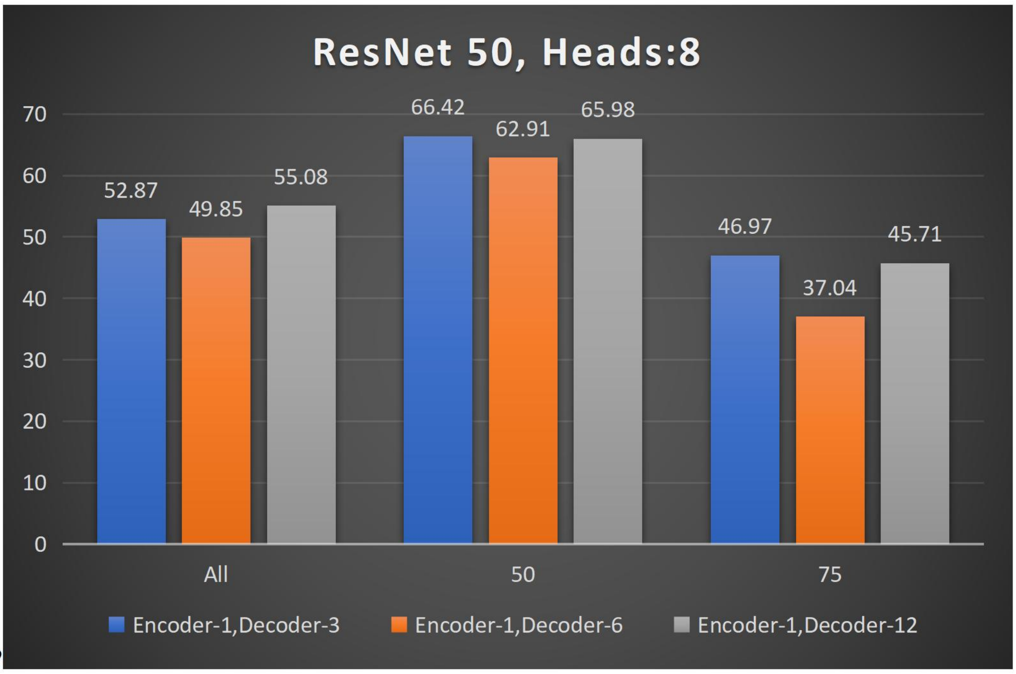


With Resnets101 with number of heads 4, Decoder 3,6&12 the detr achieves the highest mAP of 53.86, mAP-50 72.38 and mAP-75 38.44 at Decoder 3 and the lowest detr at Decoder 12 mAP 40.21 , mAP-50 58.93 and mAP-75 7.88

Table 4: *Comparative analysis using Attention heads 8 and Encoder 1*

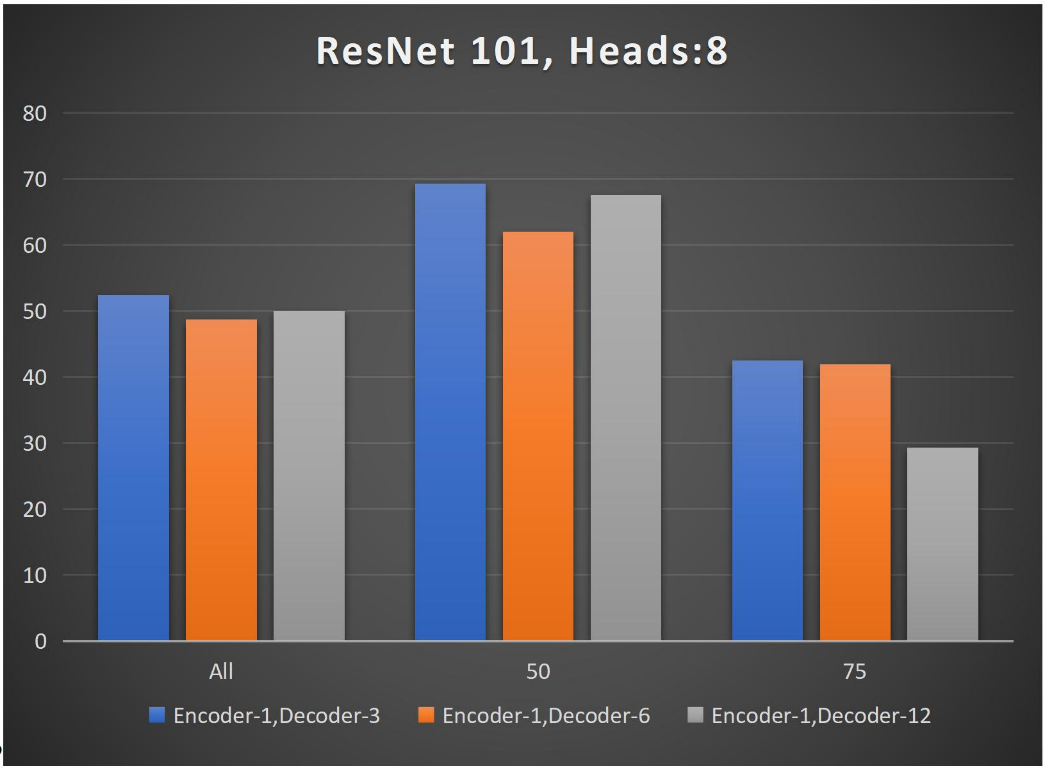
	Encoder	Decoder	Heads	All	MAP-50	MAP-75
ResNet50	1	3	8	52.87	66.42	46.97
	1	6	8	49.85	62.91	37.04
	1	12	8	55.08	65.98	45.71
ResNet101	1	3	8	52.38	69.27	42.53
	1	6	8	48.69	62.05	41.9
	1	12	8	50	67.54	29.34

Figure 4: *Bar chart representation at ResNet50 using Attention heads 8,Encoder 1, Decoder 3,6 and 12*



At Resnets50, number of heads 8, we achieve the highest mAP test at Decoder 12 of mAP 55.08 mAP-50 65.98 and mAP-75 45.71 and lowest at Decoder 6 49.85 , mAP-50 62.91 and mAP-75 37.06

Figure 5: *Bar chart representation at ResNet101 using Attention heads 8,Encoder 1, Decoder 3,6 and*



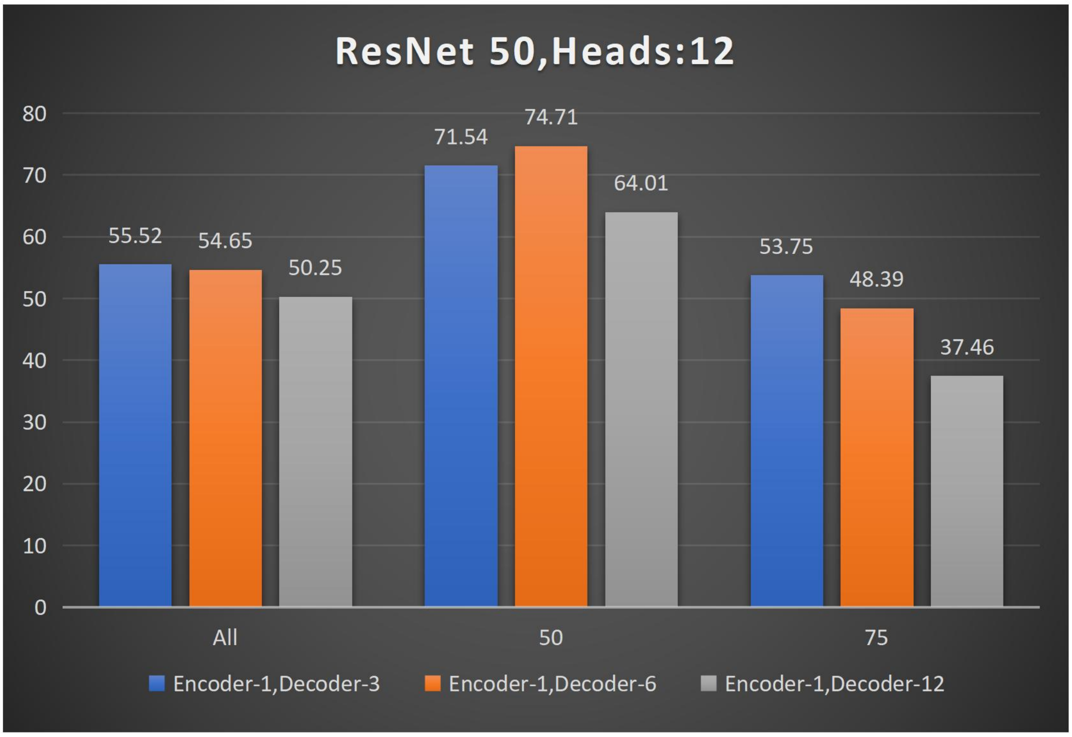
12

At Resnets101, number of heads 8, we achieve the highest mAP test at Decoder 3 of mAP 52.38 mAP-50 59.27 and mAP-75 42.53 and lowest at Decoder 6 48.69 , mAP-50 62.05 and mAP-75 41.90.

Table 5: *Comparative analysis using Attention heads 12*

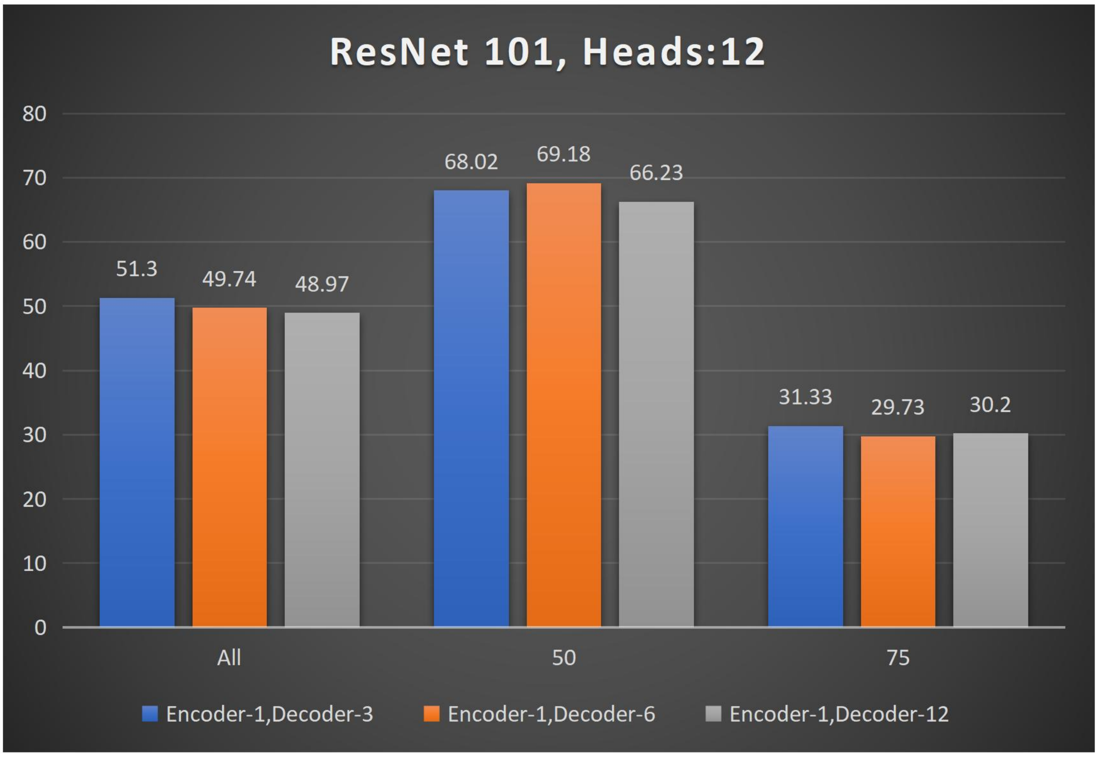
	Encoder	Decoder	Heads	All	MAP-50	MAP75
ResNet50	1	3	12	55.52	71.54	53.75
	1	6	12	54.65	74.71	48.39
	1	12	12	50.25	64.01	37.46
ResNet101	1	3	12	51.3	68.02	31.33
	1	6	12	49.74	69.18	29.73
	1	12	12	48.97	66.23	30.2

Figure 6: *Bar chart representation at ResNet50 using Attention heads 12,Encoder 1, Decoder 3,6 and 12*



With Resnets50, number of Heads 12, at Decoder 3 mAP 55.52 is the highest ,mAP-50 71.54 and mAP-75 53.75 and lowest at Decoder 6 54.65 , mAP-50 62.05 and mAP-75 41.90.

Figure 7 *Bar chart representation at ResNet101 using Attention heads 12,Encoder 1, Decoder 3,6 and*
12



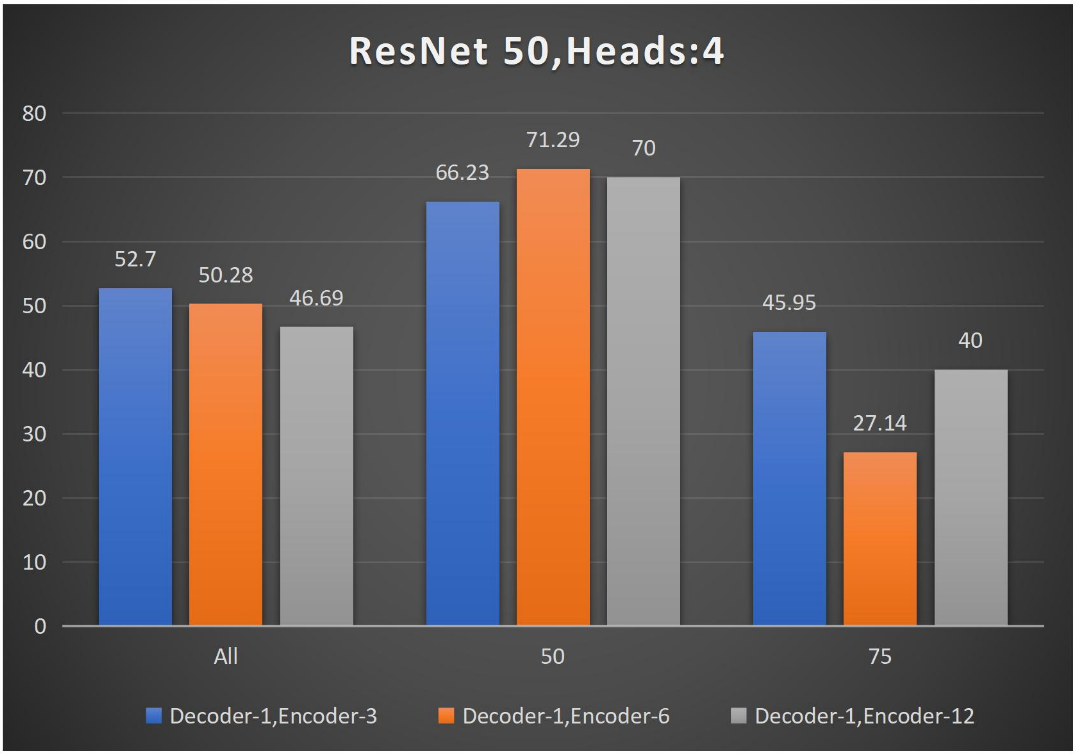
Resnets101, number of Heads 12 The detr achieves the highest mAP of 51.3, mAP-50 68.02 and mAP-75 31.33 at Decoder 3. The lowest detr at Decoder 12 mAP 48.97 , mAP-50 66.23 and mAP-75 30.2

Table 6: *Comparative analysis using Attention heads 4 and Decoder 1*

For the second scenario the Decoder's input as 1 and the encoder is between (3,6 and 12)

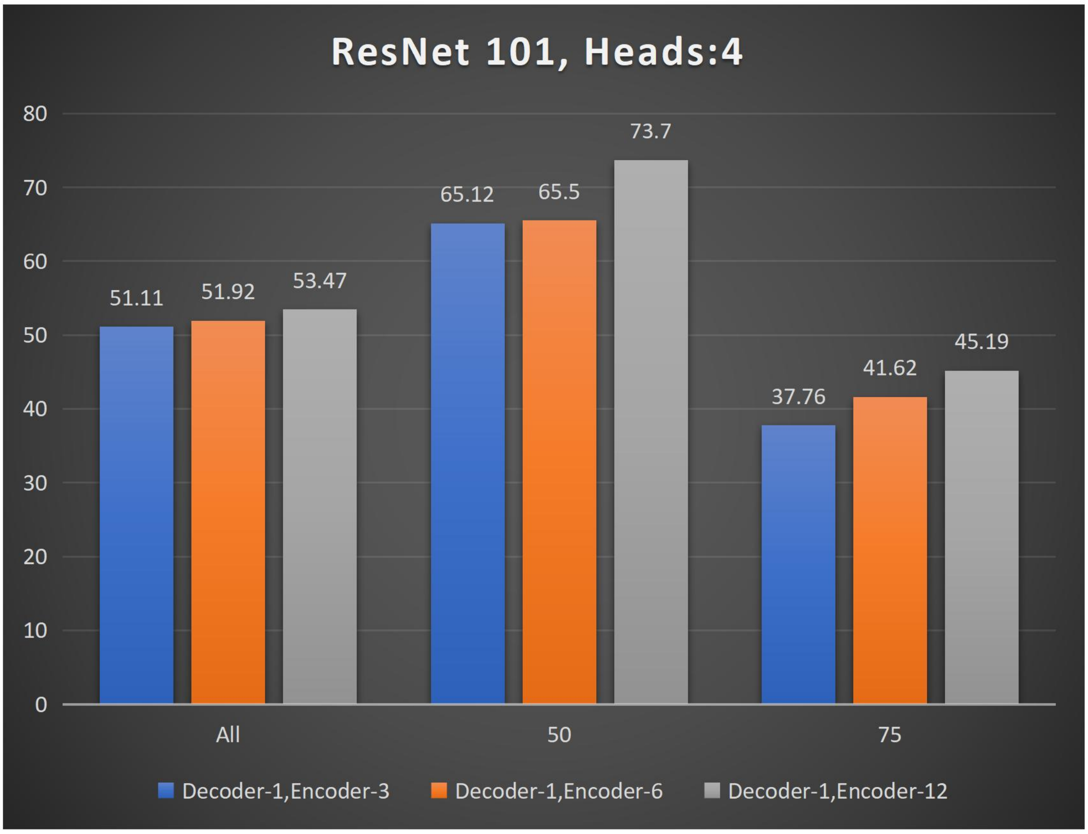
	Encoder	Decoder	Heads	All	MAP-50	MAP-75
ResNet50	3	1	4	52.7	66.23	45.95
	6	1	4	50.28	71.29	27.14
	12	1	4	46.69	70	40
ResNet101	3	1	4	51.11	65.12	37.76
	6	1	4	51.92	65.5	41.62
	12	1	4	53.47	73.7	45.19

Figure 8: *Bar chart representation at ResNet50 using Attention heads 4,Decoder 1, Encoder 3,6 and 12*



with Resnets50 number of heads 4, Encoder 3,6&12. The detr achieves the highest mAP of 52.7, mAP-50 66.23 and mAP-75 45.95 at Decoder 3. The lowest detr at encoder 3 mAP 46.69, mAP-50 70 and mAP-75 40.

Figure 9: *Bar chart representation at ResNet101 using Attention heads 4,,Decoder 1, Encoder 3,6 and 12*

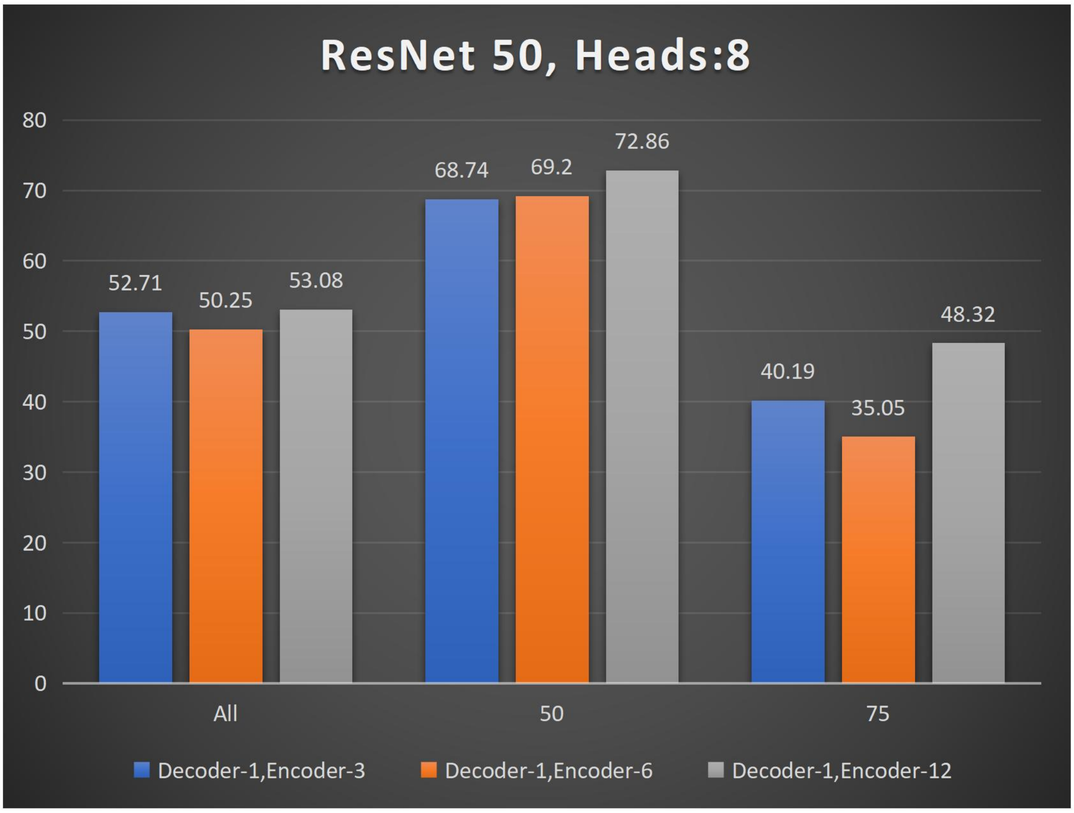


At ResNets101, number of heads mAP 53.08, mAP-50 72.86 and mAP-75 48.32 was the highest achieved at encoder 12 and mAP 46.69, mAP-50, 70.23 and mAP-75 33.75 at Decoder 6.

Table 7: *Comparative analysis using Attention heads 8 and Decoder 1*

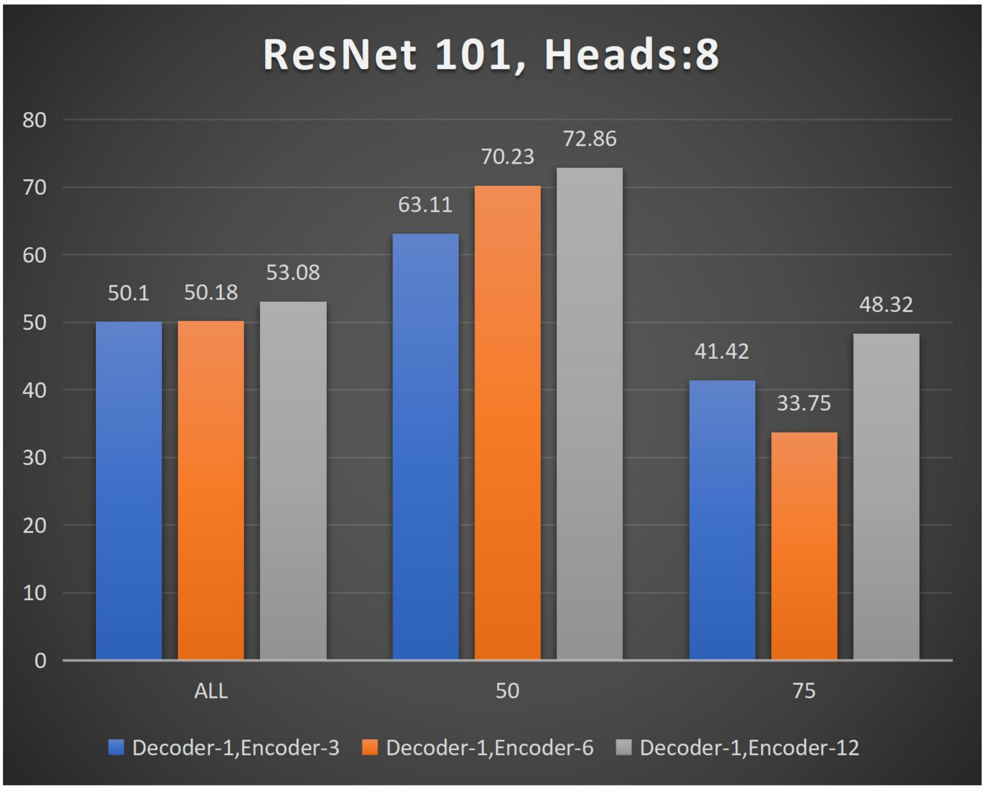
	Encoder	Decoder	Heads	All	MAP-50	MAP-75
ResNet50	3	1	8	52.71	68.74	40.19
	6	1	8	50.25	69.2	35.05
	12	1	8	54.2	70.19	44.97
ResNet101	3	1	8	50.1	63.11	41.42
	6	1	8	0.18	70.23	33.75
	12	1	8	53.08	72.86	48.32

Figure 10: *Bar chart representation at ResNet50 using Attention heads 8,Decoder 1, Encoder 3,6 and 12*



At Resnets50, number of Heads 8 the mAP 52.71, mAP-50 68.74 and mAP-75 40.19 was the highest achieved at Decoder 12 mAP 50.25, mAP-50 69.2 and mAP-75 35.05 was the lowest at encoder 6

Figure 11: *Bar chart representation at ResNet101 using Attention heads 8,Decoder 1, Encoder 3,6 and 12*

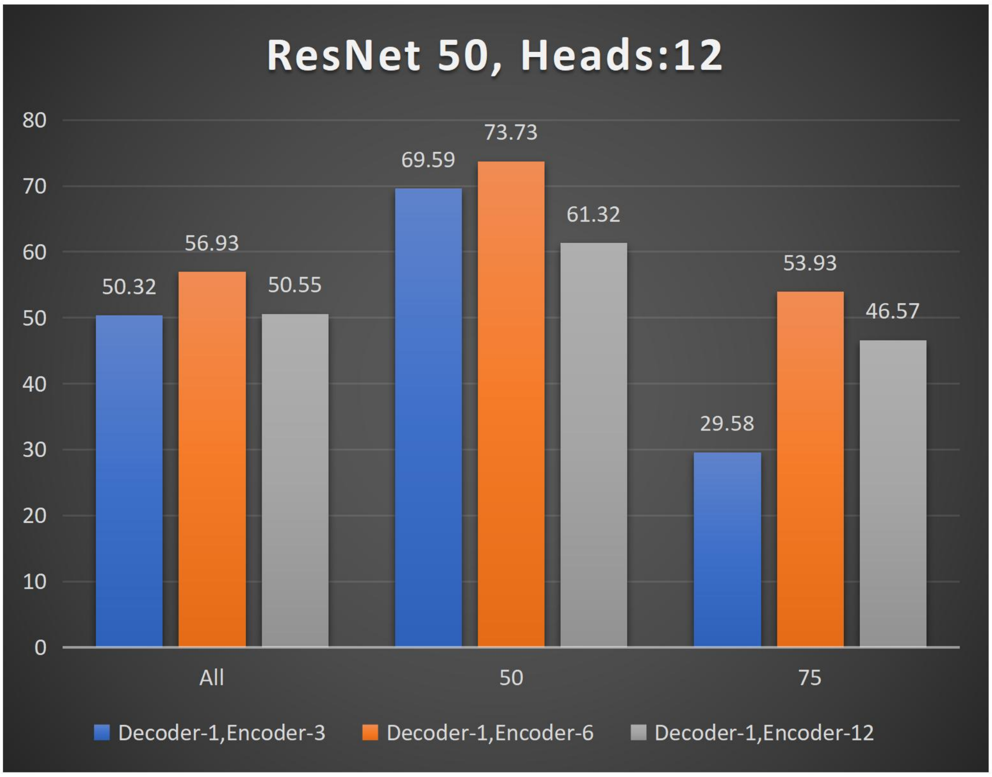


With ResNets101, number of Heads 8, mAP 53.08, mAP-50 72.86 and mAP-75 48.32 was the highest achieved at encoder 12 and mAP 49.96, mAP-50 70.23 and mAP-75 33.75 was the lowest at encoder 6

Table 8: *Comparative analysis using Attention heads 12*

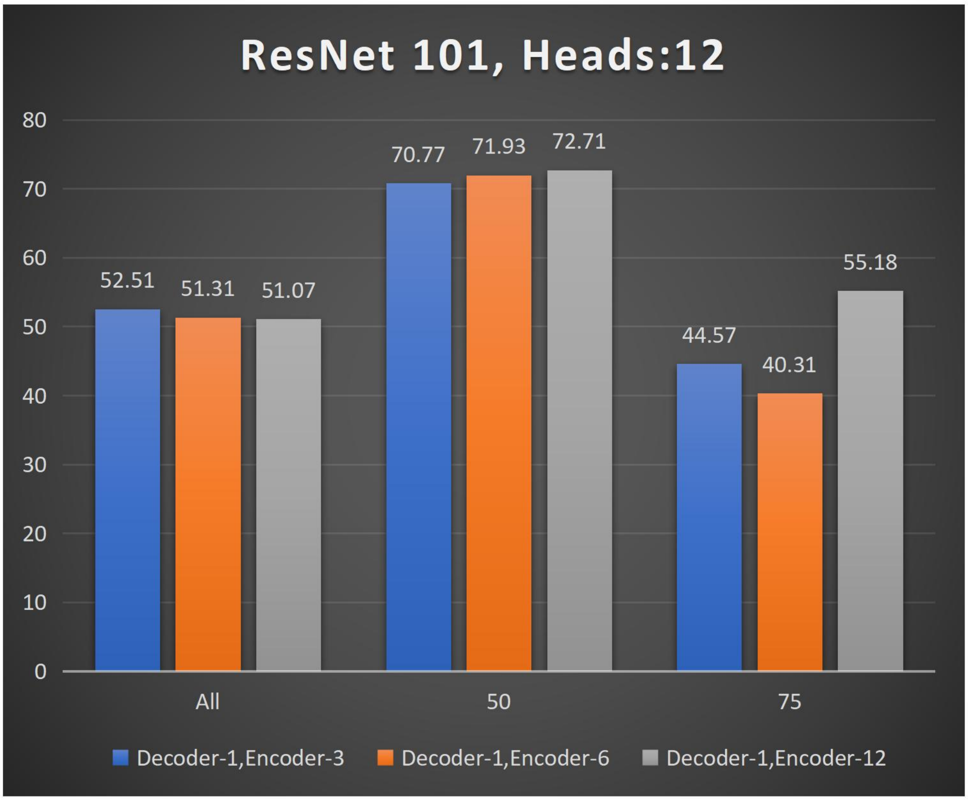
	Encoder	Decoder	Heads	All	MAP-50	MAP-75
ResNet50	3	1	12	50.32	69.59	29.58
	6	1	12	56.93	73.73	53.93
	12	1	12	50.55	61.32	46.57
ResNet101	3	1	12	52.51	70.77	44.57
	6	1	12	51.31	71.93	40.31
	12	1	12	51.07	72.71	55.18

Figure 12: *Bar chart representation at ResNet50 using Attention heads 12,Decoder 1, Encoder 3,6 and 12*



With Resnets50, number of Heads 12, mAP 56.93, mAP-50 73.37 and mAP-75 53.93 was the highest achieved at encoder 6 mAP 50.32, mAP-50 69.59 and mAP-75 29.58 was the lowest at Decoder 3

Figure 13: *Bar chart representation at ResNet101 using Attention heads 12,Decoder 1, Encoder 3,6 and 12*



At Resnets101, number of Heads 12 mAP 52.51, mAP-50 70.77 and mAP-75 44.57 was the highest achieved at Decoder 3 and mAP 51.07, mAP-50 72.71 and mAP-75 55.18 was the lowest at Decoder 12.

CHAPTER V

4.0. Conclusion

In this study, we proposed Detection Transformer, a competitive object identification method that makes use of a transformer backbone, arguing that there are viable alternative architectures to the well-researched CNN backbone that are sufficiently distinct from it to advance on challenging vision tasks. The aim of this research was to obtain a model that runs faster than the go to CNN models. The Transformer-based models have shown to be able to swiftly fine-tune to new tasks and pretrain with enormous datasets without experiencing saturation, both of which we see with DETR's in our opinion, is only the first transformer-based architecture to address the entire range of vision-related research challenges. Finally, we showed that transformer-based models, especially with short vector representations, offer a compelling alternative to convolutional backbones for retrieving specific objects in comparable scenarios. Their performance is comparable to that of networks that are considerably more complicated.

This study suggests that transformer models have proven to be a powerful tool in the field of wildfire and object detection. The ability of these models to handle large amounts of data and accurately identify patterns in images has made them a valuable asset in the fight against wildfire. The results of this project demonstrate that transformer models can be effectively trained on wildfire detection data and achieve high levels of accuracy. Additionally, the use of transfer learning with pre-trained models can further improve the performance of these models. However, there is still room for improvement in the field, particularly in terms of real-time detection and reducing false positives. Further research in these areas has the potential to greatly enhance the effectiveness of wildfire detection systems.

The future of detection transformers in wildfire detection looks promising. With advancements in technology, the ability to process larger amounts of data and train models with higher accuracy is expected to continue. Additionally, the integration of machine learning with other technologies such as drones and satellite imagery has the potential to greatly enhance the capabilities of wildfire detection systems. Real-time detection, and reducing false positives are the main challenges in this field, with more research in these areas and with the development of new techniques, it is expected that the ability to detect wildfires early on will improve. Moreover, the use of deep learning and computer vision techniques such as semantic segmentation, object detection, and instance segmentation is expected to further improve the ability of detection transformers in wildfire detection.

Another promising area for future research is the combination of transformer models with other machine learning techniques such as reinforcement learning and generative models. This could lead to the development of more sophisticated wildfire detection systems that can adapt to changing conditions and make decisions in real-time.

In summary, the use of detection transformers in wildfire detection is a rapidly evolving field with many exciting possibilities for the future. With continued research and development, it is expected that these models will play an increasingly important role in the fight against wildfires.

CHAPTER VI

REFERENCE

A. Buslaev, S. S. (2018). Fully Convolutional Network for Automatic Road Extraction from Satellite Imagery. *CoRR, vol*.

A. S. Mubarak, Z. S.-T. (2021). Smart Tourism: A Proof of Concept For Cyprus Museum of Modern Arts In The IoT Era. *2021 International Conference on Artificial Intelligence of Things (ICAIoT)*, 49-53.

Alec Radford, J. W. (2019). *r. Language models are unsupervised multitask learners. .* OpenAI blog, 1(8):9.

Alexey Dosovitskiy, L. B. (2020.). *An image is worth 16x16 words: Transformers for image recognition at scale.*

Almeida, J. S. (2022). "EdgeFireSmoke: A Novel Lightweight CNN Model for Real-Time Video Fire–Smoke Detection.". *IEEE Transactions on Industrial Informatics*, 18.

Arsha, O. I., Aman Jantan, Abiodun Esther Omolara, Kemi Victoria Dada, Nachaat AbdElatif Mohamed, & Humaira. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon 4*.

Athanasios Voulodimos, N. D. (2018). Deep Learning for Computer Vision: A Brief Review. *Hindawi Computational Intelligence and Neuroscience*.

Auwalu Saleh Mubarak, Zubaida Said Ameen, & Al-Turjman., F. (2023). Effect of Gaussian filtered images on Mask RCNN in detection and segmentation of potholes in smart cities[. *Mathematical Biosciences and Engineering,, 20*, 283-295.

Barmpoutis, P. e. (2020). A review on early forest fire detection systems using optical remote sensing. *Sensors* , 6442.

Bouguettaya, A., Zarzour, H., Taberkit, A., & Kechida, A. (2022). A review on early wildfire detection from unmanned aerial vehicles using deep learning-based computer vision algorithms. *Signal Processing*, 190.

Chen Sun, A. S. (2017). Revisiting unreasonable effectiveness of data in deep learning era. *In Proceedings of the IEEE international conference on computer vision,*, (pp. 843–852).

Chen, X. e. (2022). "Wildland Fire Detection and Monitoring Using a Drone-collected RGB IMAGE DATASET. *IEEE Access* , 121301-121317.

Cheng Chi, F. W. (2020). *Bridging visual representations for object detection via transformer decoder.* NeurIPS.

Dampage, U. B. (2022). Forest fire detection system using wireless sensor networks and machine learning. *Scientific reports*, 12.

Davies, A. H. (2022). dentifying opportunities for expert-mediated triangulation in monitoring wildlife trade on social media. *Conservation Biology*, 36(2), e13858.

Dhruv Mahajan, R. G. (2018). Exploring the limits of weakly supervised pretraining. *. In Proceedings of the European Conference on Computer Vision (ECCV)*, (pp. 181–196).

Duda R.O., H. P. (1973). *Pattern Classification and Scene Analysis.* John Wiley and Sons .

Duda, R. O. (n.d.).

Esposito, F. a. (2001). Machine learning in computer vision. *Applied Artificial Intelligence.*, 693-705.

G, S., C. K., A. B., D. G., & Prajwal. (2020). Fire Detection Using Deep Learning. *International Journal of Progressive Research in Science and Engineering*, *Volume-1,.*

G. Kumar and P. K. Bhatia. (2014). A Detailed Review of Feature Extraction in Image Processing Systems,. *Fourth International Conference on Advanced Computing & Communication Technologies,* (pp. 5-12). doi: 10.1109/ACCT.2014.74.

Gaur, A. e. (2020). Video flame and smoke based fire detection algorithms: A literature review. *Fire technology*, 1943-1980.

Ghali, R., Akhloufi, M.A., Jmal, M., Souidene Mseddi, W., & Attia, R. (2021). Wildfire Segmentation Using DeepVision Transformers. *Remote Sens.*, 13, 3527.

Ghali, R., Akhloufi, & M. A., &. M. (2022). Deep Learning and Transformer Approaches for UAV-Based Wildfire Detection and Segmentation. *Sensors, 22(5), 1977*(https://doi.org/10.3390/s22051977).

Girshick, R., Donahue, J., Darrell., Trevor, Malik, J., & Berkeley, U. (n.d.). *Rich feature hierarchies for accurate object detection and semantic segmentation.* arXiv:1311.2524.

Goss, M. e. (2020). Climate change is increasing the likelihood of extreme autumn wildfire conditions across California. *Environmental Research Letters*, 094016.

Guan, Z. X. (2022). "Forest fire segmentation from Aerial Imagery data Using an improved instance segmentation model. *Remote Sensing*, 14.

Haenlein, M. a. (2019). "A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California management review* , 5-14.

Hahn, M. (2020). Theoretical limitations of self-attention in neural sequence models. *Transactions of the Association for Computational Linguistics*, 8:156–171.

Han Hu, J. G. (2018). *Relation networks for object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,.*

Hoover, K. e. (2021). Wildfire statistics. *Congressional Research Service*.

Hosseini, A. H. (2022). UFS-Net: A unified flame and smoke detection method for early detection of fire in video surveillance applications using CNNs. *Journal of Computational Science,*, 61.

Jadon, A. A. (2020). Low-complexity high-performance deep learning model for real-time low-cost embedded fire detection systems. *Procedia Computer Science*, 418-426.

Jain, P. C. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews., 28* (4), 478-505.

Jean-Baptiste Cordonnier, A. L. (2019). On the relationship between self-attention and convolutional layers. *arXiv preprint arXiv:1911.03584,.*

Jia Deng, W. D.-J.-F. (2009). Imagenet: A large-scale hierarchical image database. *In 2009 IEEE conference on computer vision and pattern recognition*, (pp. 248-255).

K. He, X. Z. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition*, (pp. 770-778).

Katherine Hermann, T. C. (2020). The origins and prevalence of texture bias in convolutional neural networks. *Advances in Neural Information Processing Systems, 33.*

Kaul, V. S. (2020). "History of artificial intelligence in medicine." . *Gastrointestinal endoscopy* , 807-812.

Khan, S., & Khan, A. (2022). FFireNet: Deep Learning Based Forest Fire Classification and Detection in Smart Cities. *Symmetry*, 14, 2155.

Khan, S., Teng, Y., & Cui, J. (4–7 June 2021). Pedestrian Traffic Lights Classification Using Transfer Learning in Smart City Application. *In Proceedings of the IEEE 13th International Conference on Communication Software and Networks*, (pp. pp. 352–356.). Chongqing, China.

Khan, S., Teng, Y., Cui, & J. (June 2021). Pedestrian Traffic Lights Classification Using Transfer Learning in Smart City Application. *In Proceedings of the IEEE 13th International Conference on Communication Software and Networks*, (pp. pp. 352–356.). Chongqing, China,.

Khan, Z. A. (2022). Randomly Initialized CNN with Densely Connected Stacked Autoencoder for Efficient Fire Detection. *Engineering Applications of Artificial Intelligence*, 116.

Khudayberdiev, O. J. (2022). "Fire Detection Approach Based on Vision Transformer.". *Springer, Cham. International Conference on Adaptive and Intelligent Systems*, 41-53.

Kim, Y.-J. a.-T. (2022). Uncertainty assessment-based active learning for reliable fire detection systems. *IEEE Access* , 10.

Kotsiantis, S. B. (2007). Supervised Machine Learning: A Review of Classification Techniques. 249-268.

Kulkarni, A. K. (2017). *Classification of Faults in Railway Ties using Computer Vision and Machine Learning.* Virginia Tech.

LeCun, Y. B. (2015). Deep learning. *Nature 521*(https://doi.org/10.1038/nature14539), 436–444.

Li, W. (2022). CNN-transformer mixed model for object detection. *arXiv preprint arXiv:*, 2212.06714.

Li, Y. S. (2022). A Deep Learning Method based on SRN-YOLO for Forest Fire Detection. . *In 2022 5th International Symposium on Autonomous Systems*, 1-6.

Li, Y. Z. (2022). An efficient fire and smoke detection algorithm based on an end-to-end structured network. *Engineering Applications of Artificial Intelligence*.

Mahmoud, M. A. (2019). "Forest fire detection and identification using image processing and SVM." . *Journal of Information Processing Systems.*, 159-168.

Majid, S. F. (2022). Attention based CNN model for fire detection and localization in real-world images. *Expert Systems with Applications* , 189.

Marc Demange, A. D. (2022). Network theory applied to preparedness problems in wildfire managemen. *Safety Science*, 152.

Mark Chen, A. R. (2020). Generative pretraining from pixels. *In Proceedings of the 37th International Conference on Machine Learning, volume 1,.*

Martinsson, J. R. (2022). A Novel Method for Smart Fire Detection Using Acoustic Measurements and Machine Learning: Proof of Concept. *Fire technology*, 58.

McWethy, D. B. ((2019). "Rethinking resilience to wildfire. *Nature Sustainability* , 797-804.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, . . . Zettlemoyer, a. L. (2019). *Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension.* arXiv:1910.13461.

Mubarak, A. S., Al-Turjman, F., Vubangsi, M., Ameen, Z. S., Mahfudh, A. S., & Alturjman, S. (2022). Computer Vision Based Drone Detection Using Mask R-CNN. *2022 International Conference on Artificial Intelligence in Everything (AIE).* Lefkosa, Cyprus: IEEE.

Muhammad K., K. S. (2019). Efficient fire detection for uncertain surveillance environment. *IEEE Trans. Ind. Inf.*, 3113-3122.

Naser, M. Z. (2021). StructuresNet and FireNet: Benchmarking databases and machine learning algorithms in structural and fire engineering domains. *Journal of Building Engineering.*, 102977.

Nicolas Carion, F. M. (2020). *Endto-end object detection with transformers.* arXiv preprint arXiv:2005.12872.

Nicolas Carion, F. M. (2020). *Endto-end object detection with transformers.*

Pal, M. (2005). andom forest classifier for remote sensing classification. *International Journal of Remote Sensing*(DOI: 10.1080/01431160412331269698), 217-222.

Pincott, J. P. (2022). Indoor fire detection utilizing computer vision-based strategies. *Journal of Building Engineering*, 61.

Priyanka, A. a. (2022). Edge Computing for Smart Stove in Home Automation. *3rd International Conference on Smart Electronics and Communication (ICOSEC)*, 146-155.

Rekavandi, A. X. (2022). A Guide to Image and Video based Small Object Detection using Deep Learning: Case Study of Maritime Surveillance. *arXiv preprint arXiv:2207*.

Ren, S., He, K., Girshick, R., Sun, & Jian. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. *In Advances in neural information processing systems*, (pp. 91–99).

Saleh, M., Ameen, Z., Altrjman, C., & Al-Turjman, F. (2022). Computer-Vision-Based Statue Detection with Gaussian Smoothing Filter and EfficientDet. *Sustainability*.

Sebe, N. M. (2017). *Image and Vision Computing,.*

Seydi, S. S. (2022). Fire-Net: a deep learning framework for active forest fire detection. *Journal of Sensors,*.

Shi, W. e. ((2020)). "Change detection based on artificial intelligence: State-of-the-art and challenges.". *Remote Sensing*, 688.

Stay, D. (2019). *Fighting fire with science.* Alberta, Canada: nature.

Swain, A. E. (2022). Sensor Technologies for Transmission and Distribution Systems: A Review of the Latest Developments. *Energies 15.*, 19.

Toosi, A. e. (2021). A brief history of AI: how to prevent another winter (a critical review). *PET clinics* , 449-469.

Vaswani, A., Shazeer, N., Parmar, N., & Uszkoreit, J. J. (2017). *Attention is all you need.* NeurIPS.

Wang, W. J. (2022). Towards data-efficient detection transformers. *European conference on computer vision*, 88-105.

Wang, Y. X. (2022). "Anchor detr: Query design for transformer-based detector.". *In Proceedings of the AAAI conference on artificial intelligence*, 2567-2575.

Wilk-Jakubowski, J. e. (2022). High-power acoustic fire extinguisher with artificial intelligence platform. *International Journal of Computational Vision and Robotics* , 236-249.

Wilk-Jakubowski, J. S. (2022). Control of acoustic extinguisher with Deep Neural Networks for fire detection. *Elektronika ir Elektrotechnika,*, 52-59.

Wu, X. e. (2022.). A real-time forecast of tunnel fire based on numerical database and artificial intelligence. *Building Simulation*, Vol. 15. No. 4.

Xizhou Zhu, W. S. (2020). *Deformable detr: Deformable transformers for end-to-end object detection. a.*

Yang, C. Y. (2022). CNN-Transformer Hybrid Architecture for Early Fire Detection.". *In International Conference on Artificial Neural Networks*, 570-581.

Zhang, F. W. (2018). Data Driven Feature Selection for Machine Learning Algorithms in Computer Vision. *IEEE Internet of Things Journal*, 4262-4272.

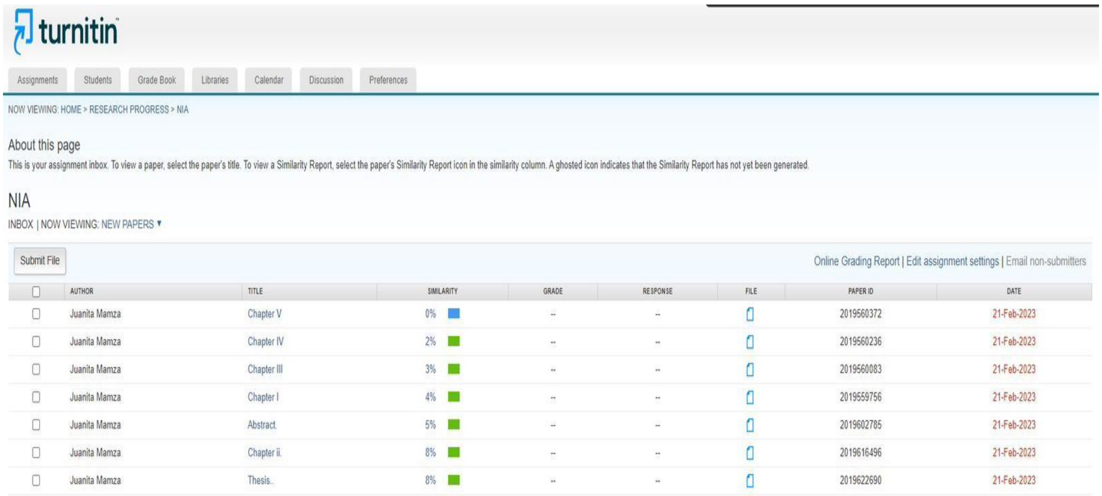
Zhang, F. W. (2018). Data Driven Feature Selection for Machine Learning Algorithms in Computer Vision. *IEEE Internet of Things journal*, (pp. 4262-4272).

Zhang, R. (2019). Making convolutional networks shiftinvariant again. *ICML.*

Zhenyang Xue, H. L. (2022). A small target forest fire detection model based on YOLOv5 improvement. *Advances in Forest Fire and Other Detection Systems*, 13.

Appendix X

Turnitin Similarity Report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APPENDIX 2
CURRICULUM VITAE

CURRICULUM VITAE

Juanita Jidai Mamza in 2021, received a bachelor's degree in Computer Engineering from Near East University. Juanita Jidai Mamza is a master's student at Near East University studying Artificial Intelligence Engineering.

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Near East University Bachelors of Computer Engineering Dates 2017-2021

<u>WORK EXPERIENCE</u>

Galaxy backbone, Nigeria— Intern **August *2019 to October 2019***

- Provided standard reporting and analysis with the use of Microsoft Excel
- Repairing of computer systems
- Trouble shooting and networking
- Fixing of broadcast that occurred using flukes
- Reconfiguring switches and setting up New Ip addresses to various sectors.

<u>SKILLS</u>

- Telecommunication skills,
- MySQL workbench
- HTML, CSS, JS
- JS REACT
- Project management.